PERCEPTOR:
A Model for Product Design

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ABSTRACT

A model and measurement methodology is proposed to aid managers in designing new frequently purchased consumer products. The model is structured as a trial and repeat process that produces an estimate of long run share for a new brand. Physical and psychological product attributes are linked to the trial and repeat probabilities through multidimensional scaling procedures. Perceptual maps of existing brands with ideal brand positionings are derived. The product design determines the new brand's position in the perceptual space and the distance from the new brand to the ideal brand specifies its probability of purchase.

Measurement and estimation procedures are discussed. Predictive and structural tests of the model are reported and a process for managerial implementation is presented. The outputs of the model are an understanding of the perception, preference, and purchase process, a framework and procedure for measurement, a structure to use in interpreting experimental results, and a tool for estimating the market share for alternate new brand designs.

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INTRODUCTION

Developing new frequently purchased consumer products may be viewed as a process of:(1) creating and designing new product concepts, (2) screening new brands, (3) test marketing, and (4) national introduction. Many models have been built and used in the screening and testing stage, but few exist which aid in design.[1] Yet this is the point at which the product comes into existence as a physical and psychological entity. This paper represents a description of an effort to determine if a model and a related measurement methodology can be useful to managers in the design phase of frequently purchased consumer products.

In a typical firm, the design process usually is initiated by an idea originating from introspection on the market or consumers, R & D, product or packaging technology, or competitor's new products. Other triggers to innovation occur when a product class is identified that looks attractive because it is growing rapidly, has not been subjected to innovation - a "sleepy" category, or because a competitor has achieved success in the product class. After initiation of the design process, rough concept descriptions are presented to consumers for their reaction. Usually likeability, interest, uniqueness, intent to try, and responses to open ended questions are obtained. At this time the strengths, weaknesses, and levels of satisfaction of existing products may be measured to identify more specifically openings for new products and potentially differentiating features. Typically, consumer group discussion sessions are conducted to understand some of the behavioral aspects surrounding the product's consumption and consumers' reactions to concepts. From this information a best concept and physical product emerges. This product is usually given to consumers to determine how the product compares to existing brands after in-home usage. The output of this sequential process is a physical new product and what is termed as a designation of the "product positioning". Next, advertising copy is developed and tested. The concept then undergoes formal screening and test marketing before introduction.

The brand creation and design process is a rather unstructured problem and existing procedures seem to provide ample opportunity for improvement. This paper outlines an attempt to bring additional structure and quantitative analysis to bear on the creation and design process by the use of a mathematical model. Recent developments in multi-dimensional scaling of psychological data offer an approach to such a model.

One of the first authors to explicitly consider the potential of non-metric multi-dimensional procedures in marketing was Stefflre.[2] He developed perceptual maps of existing market structures based on similarity judgments and considered the notion of introducing brands in areas of the maps where other brands did not exist.[3] Stefflre's work was followed by the research of many others. Green, Carmone, and Rao have provided an excellent summary of this multi-dimensional scaling literature.[4] Pessimier has summarized the related research on linear additive models in multi-attribute choice theory.[5]

The work reported here utilizes existing methods of scaling in a model structured as a trial and repeat purchase process. Product positioning is linked to the process parameters through multi-dimensional scaling procedures. The outputs of the model are an estimate of the market share for alternate new brand positions and an understanding of the perception, preference, and purchase process underlying the product positioning decision. The goal of the model is to aid managers in the creation of new frequently purchased consumer products. The model is not designed to forecast the demand for the new product since this could be done only during the later test market stage of development. The model is intended to be used as a framework for measurement and a structure for management to use in design, evaluation, and refinement of frequently purchased consumer products. The remaining sections of this paper will describe the model structure, measurement, estimation, predictive testing, and managerial implementation.

MODEL STRUCTURE

Overall Flow

The model is structured around the generation of an estimated long run market share for the new product. This structure is chosen because long run share provides a good basis for evaluating the potential of a concept, method of selecting between alternative concepts, and criterion for use in refining concepts.

The overall model flow described in Figure One is used to specify long run share. Target group members try the brand with a specified probability and then repeat purchase behavior is modeled as a Markov process. Formally, the market share of the new brand is the product of the ultimate trial fraction and the equilibrium share of purchase of the new brand among those who have used the brand.

(1) $$m = ts$$

m = long run market share

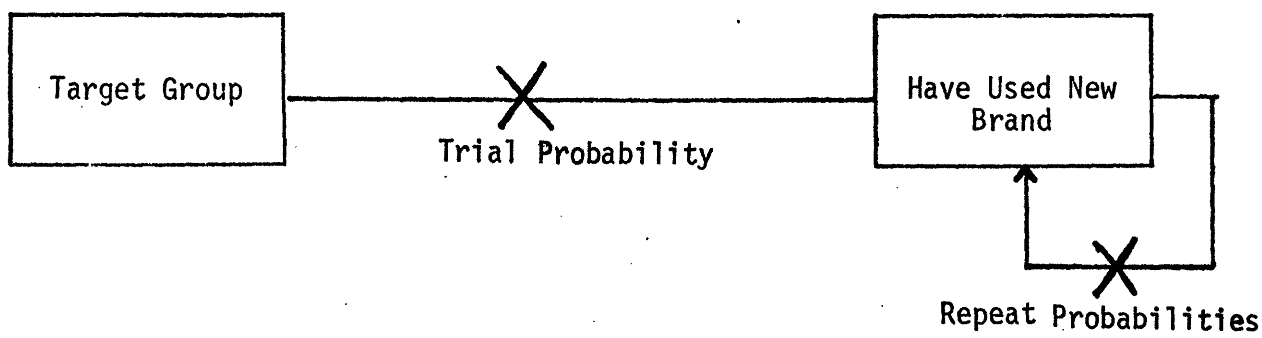
t = fraction of the target group who ever try the new brand, $0 \leq t \leq 1.0$

s = market share of purchases of new brand among those who have ever tried the brand

This is similar to the equation proposed by Parfitt and Collins to predict new product performance based on test market consumer panel data.[6] They reported a high level of accuracy in predictive tests of 25 brands. At the concept stage of development, consumer purchase panel data is not feasible to collect, but surrogate measures for trial can be measured in a group which has been made aware of the concept and repeat probabilities can be obtained after the product has been used by a

FIGURE ONE

Overall PERCEPTOR Structure



sample of consumers. These concept and usage test measures will be used to derive the long run trial (t) and the market share of those who have tried (s).

The ultimate trial is defined as:

$$t = qwv \tag{2}$$

q = ultimate probability of trial given awareness and availability

w = long run aided awareness of new brand

v = long run percent of all commodity availability of new brand (i.e., percent of stores carrying brand weighted by sales volume of store)

The propensity to try given awareness and availability (q) is measured by the observed trial fraction in a group made aware of the new concept.

The market share of those who have used the brand is modeled as the equilibrium of the two state Markov process shown in Figure Two.[7]

$$s = p_{21} / (1 + p_{21} - p_{11}) \tag{3}$$

This Markov formulation assumes that the frequency of purchase of the new brand is the same as existing brands. This assumption can be relaxed somewhat by multiplying the share (s) by an index to reflect relative usage rates of brands. If heterogeneity exists across consumers rather than brands, consumers could be grouped into classes on the basis of their usage rates (heavy, medium, and light) and separate transition matrices estimated for each group. In this situation the overall share would be the average of each class weighted by its usage

FIGURE TWO

Markov Process Matrix for Those Who Have Used Our Brand

		Purchase n+1	
		Purchase of our brand	Not purchase of our brand
Purchase n	Last Purchase Our Brand	p_{11}	p_{12}
	Last Purchase Not Our Brand	p_{21}	p_{22}

p_{ij} = probability of moving from row i to column j in the relevant interpurchase interval, $0 < p_{ij} < 1.0$.

rate. Equation 3 also assumes that the consumer will find the new product at the next purchase opportunity. This is reasonable since the consumer has already purchased the product. Unless the product goes out of stock or is dropped by the retailer, it would still be available if the consumer returned to that store. Although the Markov model assumptions may be a bit restrictive, a more elaborate shopping and diffusion model with additional states to represent detailed purchase histories and levels of usage is not proposed. It is difficult realistically to measure higher order repeat rates, frequency of purchase, and store shopping patterns at the concept stage of product development. In cases where they could be measured, a simple version of SPRINTER could be used to estimate long run share.[8]

Next the linkages of product positioning to the trial and repeat probabilities are defined by considering joint space (perception and preference) maps and their relationship to probability of trial and repeat.

Trial Model

Perception and Preference: First, notation to describe joint space perceptual maps is defined. Let

x_{by} = coordinates of brand b on dimension y for the perceptual map of those who have not tried our brand, but who are aware of the concept (b= 1,2, ...B, where B = new brand; y = 1,2, ...Y)

I_y = coordinates of average ideal point on dimension y for map of those who have not tried our brand but who are aware of the concept.

The coordinates of each brand could be derived by either non-metric scaling of similarity data or factor or discriminant analysis of brand rating data. For maps developed by factor analysis, the following relationship will result:

$$(4) \quad x_{by} = \sum_{a=1}^{A} f_{ya} \, r_{ba}$$

f_{ya} = factor score coefficient for dimension y and scale a $(a = 1, 2, \ldots A)$

r_{ba} = standardized average rating of brand b on scale a.

This is a useful relationship since a new brand position can be specified by changing the original scale ratings for a brand, rather than by specifying the position on the aggregated dimensions directly. Ideal point coordinates (I) can be obtained via Carroll and Chang's PREFMAP or from the factor analysis of ratings of an ideal brand on product rating scales.[9]

Heterogeneity of perception and preference can be considered in the model by subdividing the total group into homogeneous subgroups and treating each separately. Each subgroup is indexed by a subscript. Heterogeneity of perception is handled by assigning a subscript to x and I to represent perceptually homogeneous groups. These groups could be defined by: (1) clustering individuals based on their weights from an INDSCAL analysis of nonmetric data, (2) clustering based on factor scores derived from rating data, or (3) by a Q-type factor analysis.[10] The choice of the particular procedure depends upon the specific data collection procedures.[11] Similarly, a subscript could be added to I to reflect the average ideal points of clusters of people with homogeneous preference structures. Since PREFMAP can derive the coordinates of ideal points at the individual level, the individual ideal coordinates can be aggregated into homogeneous groups by clustering the individuals on the basis of the distances between the brands and the individual ideal points. An alternate procedure would be to cluster the original preference data if it were metric. Finally, an ideal point subscript could be added to refer to type of product usage condition. Ideal points may vary for the same products depending on the use. For example, preferences may be different for wine served when guests are present versus wine served when no guests are present, even though the perceptions of brands may be similar. Green and Rao found significantly different preference ratings for breakfast rolls depending on what other foods were served or if it was a light or heavy breakfast.[12]

Probability of Purchase: The probability of trial is postulated to be a function of the squared distance between the ideal point and the new brand. This implies that as a brand is positioned closer to the ideal point, its probability of choice increases non-linearly. The squared distance function is the simplest of many non-linear functions and is appropriate over the range of existing data:

$$(5)\quad q = \alpha_0 + \alpha_1 d_B^2$$

q = probability of trial of new brand given awareness and availability, $0 \le q \le 1.0$

α_0, α_1 = coefficients to be determined empirically

d_B^2 = squared distance from ideal point to the new brand(denoted by b=B) on map for those who are aware but have not yet used our brand.

In the general case, the distance on the map for those people who are aware but have not tried our product is:

$$(6)\quad d_b^2 = \sum_{z=1}^{Z} h_z (x'_{bz} - I'_z)^2$$

x'_{bz}= rotated coordinates of brand b on dimension a (z = 1,2, ...Z), where

$$(6a)\quad x'_{bz} = \sum_{y=1}^{Y} x_{by} T_{yz}$$

T_{yz}= cosine rotational transform of dimension y to z (obtained from PREFMAP)

x_{by}= coordinates of brand b on dimension y on map for people aware of new concept.

I'_z = rotated coordinates of ideal point on dimension z, where:

$$(6b)\quad I'_z = \sum_{y=1}^{Y} I_y T_{yz}$$

I_y = coordinates of ideal point on dimension y.

h_z = importance weights for dimension z (obtained from PREFMAP; h_z may be negative).

By allowing rotation and weighting, these equations provide sufficient flexibility to fit empirical phenomena. Equation 6 is the distance equation of PREFMAP phase I. In PREFMAP phase II, no idiosyncratic rotation is done and in phase III axes are equally weighted so in this case the distance equation is simplified to the Euclidean form.

The output of the trial model is the ultimate trial probability given awareness and availability. When multiplied by estimated long run awareness and availability, it provides the estimated long run fraction of the target group who will try (see equation 2).

Probability of Repeat

The probability of a repeat purchase after usage of the new brand is determined analogously to the trial probability by the position of the new brand relative to the ideal point on a perceptual map, but the coordinates and ideal points are derived from data obtained from people who have used the new brand. The repeat purchase probability is:

$$(7)\quad p_{11} = \tilde{\alpha}_0 + \tilde{\alpha}_1 \tilde{d}_B^2$$

p_{11} = probability of repeat purchase (see Figure 2).

$\tilde{\alpha}_0, \tilde{\alpha}_1$ = coefficients empirically determined.

$\tilde{d}_B^2$ = distance squared from ideal point to new brand after use(for definition see equation 6 with brand coordinates from map of those who have used the brand).

$$0 \leq p_{11} \leq 1.0$$

The probability of purchase if the new product is not chosen (p_{21}) is determined empirically.

Sources of New Brand Share

After substituting the trial and repeat probabilities in equation 1, an estimate of the share of the new brand is obtained. Managerially it is important to know which brands will lose the most share to the new brand. This will affect competitive reaction and is critical if the firm introducing the new brand also has other brands in the product class. To estimate the source of the market share, it is assumed that share will come from the brands that are most widely evoked. A brand is defined as evoked by a consumer if it has been used, if it would be considered at the next purchase, or if it is rejected as a purchase alternative. These brands are called the evoked set. The new product share is obtained from brands proportional to their appearance in consumer evoked sets and inversely proportional to their distance from the new brand.

$$(8) \quad k_b = m\left((e_b/D_{bB}^2) \Big/ \sum_{b=1}^{B-1} (e_b/D_{bB}^2)\right)$$

k_b = loss in market share of existing brand b

m = market share of new brand

e_b = fraction of people who have brand b in their evoked set.

D_{bB}^2 = distance squared from brand b to new brand B in users map.

$$(9) \quad D_{bB}^2 = \sum_{z=1}^{Z} \tilde{h}_z (\tilde{x}'_{bz} - \tilde{x}'_{Bz})^2$$

$\tilde{x}'_{bz}$ = rotated coordinates of brand b on dimension z (see equation 6a) on map for people who have used our brand

$\tilde{h}_z$ = importance weights for dimension z in users map ($\tilde{h}_z > 0$)[13].

This completes the model description. The next sections will describe the measurement methodology and estimation procedures.

MEASUREMENT

To supply data for the model, four studies are proposed: (1) exploratory, (2) base line, (3) concept awareness, and (4) in home placement. This section will describe the content of each survey and the next section will describe how the data have been used in estimating the model's parameters. This section describes the overall approach, but in a specific product case, good marketing research judgment is usually required to specify the final research instruments.[14]

Exploratory Survey

The first task of the exploratory survey is to find the size and composition of consumers' evoked sets. Table One gives the average size of the evoked set, total number of brands evoked, and the number of brands necessary to account for 80% of the sales in six product classes. These are survey

TABLE ONE

Evoked Set

Product	Median Evoked Set Size	Total Number of Brands Evoked	Number of Brands Necessary to Account for 80% of Market
Canadian Beer	7	15	7
Aerosal Deodorant	3	20	6
Skin Care Product	5	30	12
Over the Counter Medicinal Product	3	20	5
Pain Relief Product	3	18	6
Antacid	3	35	6

results based on interviewing approximately 100 people in each product class. In the first case the evoked set is of reasonable size and the composition is similar when examining the major share of the market (80%). Therefore a standard questionnaire was developed using anchor point similarity judgments, paired comparison preference evaluations, and brand ratings on a set of scales for eight specified brands. In the other five classes shown in Table One, the evoked set sizes are small and the composition varies. In these cases paired comparison similarity and preference judgments and brand ratings were collected only for the evoked brands. The evoked set size and composition are important considerations in determining the method of measurement.

The next task in the exploratory survey is to find the semantics of consumers. Personal interviews in which consumers are asked to contrast the two most similar and different brands in each triad of evoked brands or the analysis group session transcripts are two sources of semantics.[15] Personal interviews that probe usage habits, reasons for use, and demographics supply input for the design of the questionnaire and indications of consumer segments. The final step in the exploratory procedure is to pretest the similarity measurement method and obtain bi-polar brand rankings on the scales generated by the semantics procedures. Bi-polar ratings on a 1 to 7 scale are used to measure perception. Ratings on a scale from best to worst for an attribute are not used since these imply evaluative judgments. These evaluative judgments are captured in preference, and therefore should not be used in ratings that are designed to support estimation of perceptual maps.

The outcome of the exploratory survey is a procedure to collect similarity, rating, and preference data along with an understanding of brand usage and consumer segmentation phenomena.

Base Survey

Next a survey of target group members is conducted to: (1) obtain their evoked set, (2) similarity judgments, (3) ratings of brand on the semantic scales, (4) preference evaluations, and (5) their brand choice. The brand choice is obtained by giving the respondent a sum of money (say two dollars) and asking him to select the brand he would like to buy. In addition, other consumer measurements not explicitly required by the model may be taken for diagnostic purposes. This base survey becomes the input for mapping of the existing market and for the generation of a crude specification of new product concept for the market.

Concept Awareness Survey

The concept awareness survey is conducted on a group of people who are made aware of an initial new concept by a picture of the product and a concept statement or a rough ad copy execution. The data specified in the base survey is collected for this group for the new and existing brands. These data become input to the trial model.

In Home Placement Survey

If the brand idea looks reasonable after the concept survey, a group of people are given the physical product and the items of the base survey are measured again. One additional item must be collected. For those who do not choose the new brand again, intent to buy the new brand is obtained on a seven point scale. These data are needed in the repeat model to estimate the probability of repeat purchase if the last brand purchased is notthe new product (p_{21}).

ESTIMATION

This section describes the procedures to convert the survey data into estimates of map coordinates (x), ideal points (I), and probability of purchase parameters $(\alpha_0, \alpha_1, \tilde{\alpha}_0, \tilde{\alpha}_1)$. Examples of the procedures are provided based on the analysis of Canadian beers.

The data base consisted of personal interviews with 113 college men.[16] Data from the first 45 respondents were used for estimation and data from 68 respondents were saved for split sample testing. The 45 respondents used for estimation were interviewed twice. The first interview was exploratory and constructs were elicited by Kelly's procedure. The evoked set was defined as the union of the brand last used, brands they would consider buying, brands they would not consider buying, the brand usually purchased, and the brand that would be purchased if the usual brand was not available. In this case the evoked set was of acceptable size and the composition was similar so a standard questionnaire could be used (see Table One). Anchor point similarity judgments and brand ratings were obtained. Constant sum preference data were collected by asking respondents to split 100 points between each pair of brands in proportion to their preference. This allows the formation of a metric preference scale.[17] The interview ended with each respondent selecting a 12 pack of beer as his reward. This was a pseudo brand purchase. These data represent an example of the exploratory and base survey data described in the measurement section of this paper.

Perception

First, the possible existence of heterogeneity of perception should be examined. This could be done by the use of INDSCAL on the similarity data, Tucker and Messick's program, or clustering of factor scores.[18] For example, in this study after a factor analysis of the brand ratings data, the factor scores of each individual and each brand were clustered. Clustering was done with the Howard-Harris program and five clusters accounted for only 30% of the total variation.[19] This did not provide evidence that respondents could be divided usefully into a small number of groups with homogeneous perception. The idiosyncratic heterogeneity was aggregated into one group, since defining a very large number of groups would lead to small unworkable sample sizes.

After dealing with the issues of heterogeneity, maps are then developed by metric scaling of brand ratings data or by non-metric scaling of similarity data. Both approaches were used in the beer study.

First, perceptual maps were derived by factor analysis of the two way matrix of individual brand ratings by scale constructs.

Each row of the matrix represented the ratings for a particular individual for a particular brand. Only brands evoked by each respondent were included. Factor analyzing such as matrix will produce an estimate of the underlying perceptual dimensionality. This is an especially attractive procedure when evoked sets are small and composition varies since the matrix will be of reasonable size (the number of rows=number of respondents times average number of brands evoked and number of columns=number of scales) and a good estimate of the underlying dimensions can be obtained if it is assumed that the underlying dimensionality is not a function of the specific brands evoked. The factor loadings in the beer case were obtained from a common factor analysis with Biomed program, BMDX72. Dimensions were retained only if their eigen values were greater than one. The cumulative total explained variance and the associated eigen values are given in Table Two.

TABLE TWO

Overall Factor Analysis Dimensions

	1	2	3
Cumulative Variance	.34	.54	.57
Eigen Values	5.80	3.40	.534

This indicates two dimensions were sufficient to represent the data and the explained variance levels were adequate for common factor analysis (.54 of the overall variance was .89 of the common variance).

Figure 3 shows the varimax rotated factor loadings plotted on the two dimensional space. The horizontal dimension has social connotations of popular, lively, modern, and swinging. The vertical dimension is taste oriented and associated with strong, sharp, and heavy taste.

Brands were represented on the map by their average factor scores. Figure 4 shows the overall configuration. The brands are perceived as very different in the taste/social space. Dow is strong and old fashioned, while Labatt has an intermediate taste and is modern and young.

In order to generate maps from the similarity judgments, TORSCA-9 was used to process the average similarity data.[20] Table Three gives Kruskal's "stress" measure of goodness of fit and the estimated probability

FIGURE THREE: Factor Loadings

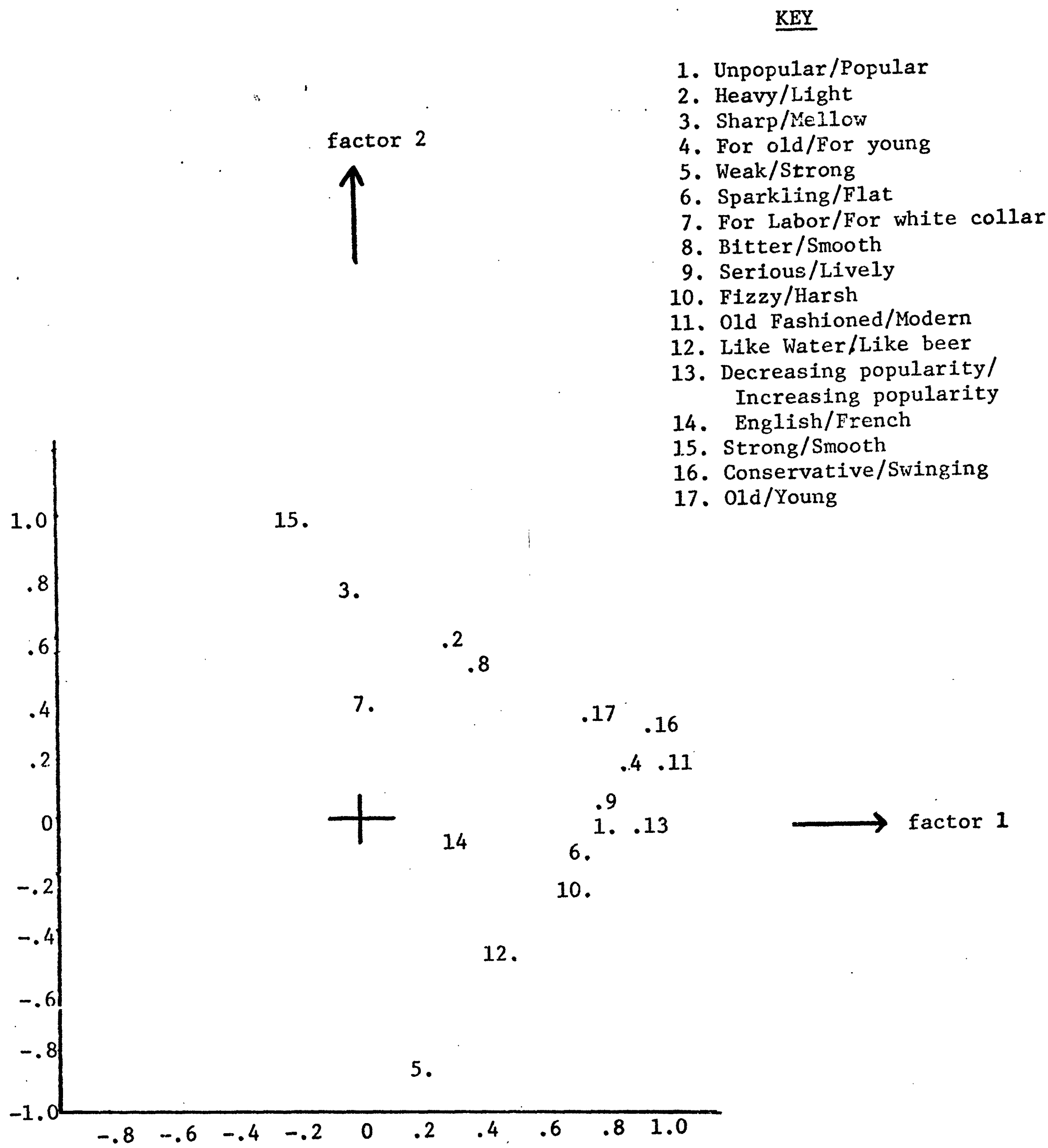
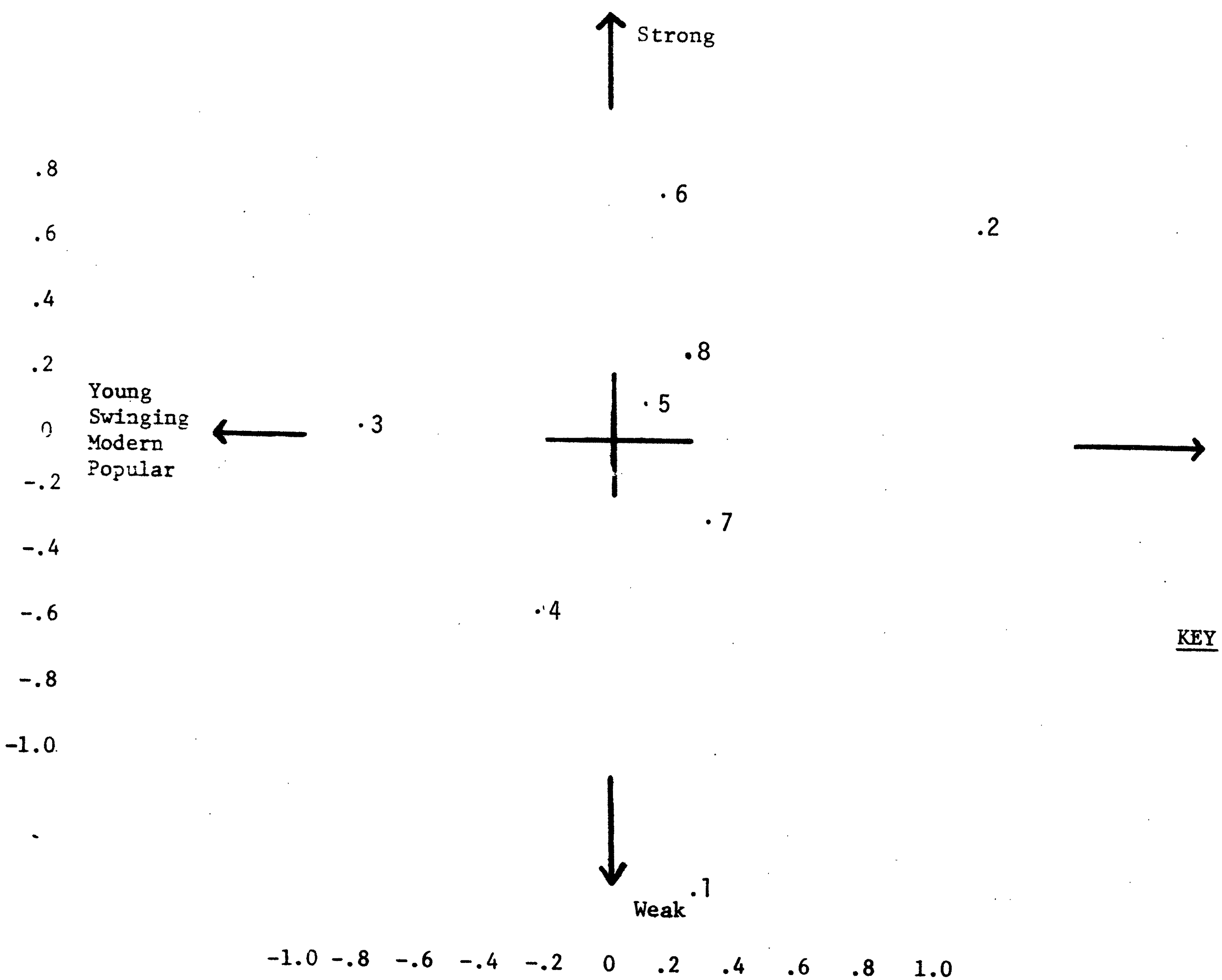


FIGURE FOUR: Average Factor Scores for Brands



KEY

1. Heidelberg
2. Dow
3. Labatt
4. Laurentide
5. O'Keefe Ale
6. Molson Export
7. Pilsener Bleu
8. Molson Canadian

that such a stress value or less could have been generated from random data. No formal statistical test exists for non-metric scaling, so the probabilities were obtained from Klahr's Monte Carlo simulations of random data with Kruskal's multidimensional scaling program (M-D-SCAL III).[21] The TORSCA and M-D-SCAL algorithms are similar and they have given very similar maps in comparative tests, so Klahr's results are reasonable to consider for this case.[22] The significance of fits were not very good. None of the solutions were significant at the 10% level, but the best level of significance was for two dimensions. To provide a basis of comparison, a similarity measure was derived from the factor ratings by summing, across all scales, the difference between the ratings for each pair of brands. The TORSCA results based on the derived measures are reported in Table 3.[23] The fits based on the derived similarity judgments were much better. The stimulus configuration from the direct and derived similarity measures were not similar. Even after rotation to achieve a best fit, only a correlation of .28 existed between the interpoint distances. In this case, brand ratings provided a better representation of perception than similarity judgments. In both similarity analyses, two dimensions were indicated as most statistically significant. This agreed with the factor analysis result and indicated that probably no major scales were omitted from the brand ratings. If non-verbal perceptual dimensions existed or scales were omitted, the similarity analysis would provide additional dimensions and either the similarity maps would be used or attempts would be made to discover a rating scale to measure the new dimension. In the beer case two perceputal dimensions were sufficient and the brand rating data provided the best perceptual measurement.

TABLE THREE

TORSCA Goodness of Fit for Similarity Data

	Stress	Approximate probability of occurring from random data (i.e. significance)
Direct Similarity		
3 dimensions	.049	25%
2 dimensions	.123	15%
1 dimension	.339	20%
Derived Similarity		
3 dimensions	.007	5%
2 dimensions	.060	3%
1 dimension	.320	20%

Preference

Given an average perceptual map and individual preference judgments, PREFMAP can be used to derive an ideal point such that the squared distance from this point to each brand best recovers the preference data. PREFMAP estimates an ideal point for each individual under: (1) idiosyncratic rotation and differential weightings (Phase I), (2) no idiosyncratic rotation but with idiosyncratic differential weighting (Phase II) or (3) no idiosyncratic rotation or differential weighting (Phase III). A fourth option is to estimate a vector of increasing preference rather than an ideal point.

Figure Five shows the overall perception map with the average ideal points (across all individuals) for the first three phases of PREFMAP applied to the beer data. In this figure the vectors indicate orientation of axes, direction of highest preference, and the axes weights. Phase I was a saddle point and Phase II and III were minimum points on the preference surface. Table Four reports the goodness of fit for the average preference vector and the average of individual correlations of actual and predicted preference.

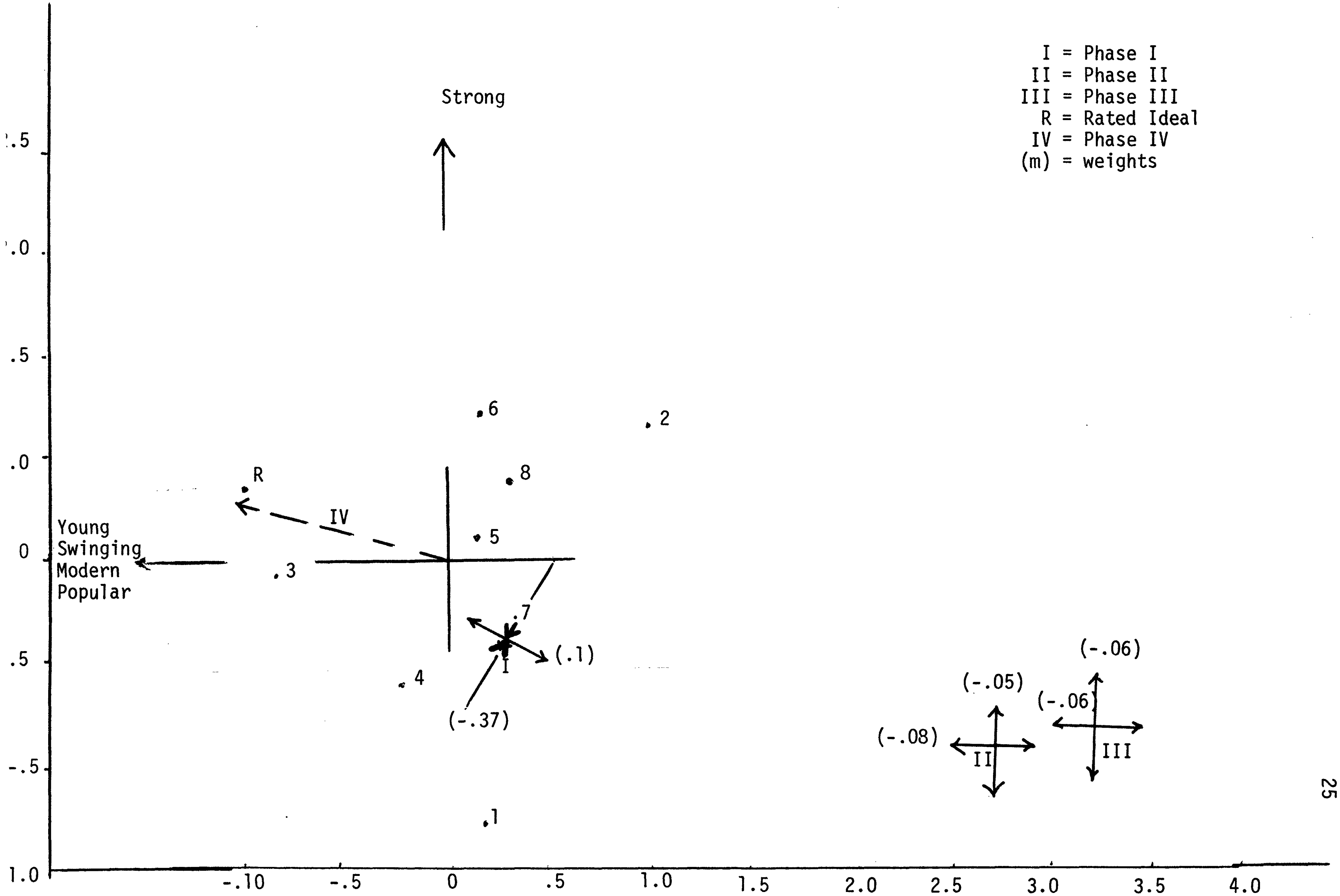
TABLE FOUR

Overall PREFMAP Goodness of Fit

Phase	Correlation of Predicted and Observed Average Preference (n= 8 brands)	Average of Individual Correlations of Observed and Predicted Preference (n = 45 individuals)
1	.98	.87
2	.953	.82
3	.952	.73
4	.93	.66

In all phases the average preference recovery is good, but the average individual recovery falls from explaining 76% of the variance in phase one to 43% in phase four. PREFMAP supplies some F statistics to test the significance of the differences between phases. However, in this case the degrees of freedom were so small ($n_1 = 4$, $n_2 = 3$) that significance would be difficult to achieve. Therefore, a decision was made to continue the analysis with phase one since the best fits would be required to obtain reasonable distance functions for the choice model. The appropriate-

FIGURE FIVE: Overall Ideal Points



ness of this judgment was examined in the probability of purchase analysis.

Preference may not be homogeneous. In the beer data, the Phase II standardized distances of brand to individual ideal points were clustered. Two groups accounted for 57% of the overall variation. The respondents in each cluster were re-submitted to PREFMAP to obtain the Phase I to IV average ideal points for each cluster. The ideal points for each cluster were very similar (e.g. phase IV direction cosines of .99,- .20 and .99,-.14), so although two clusters could be justified by the data, the managerial significance of this disaggregation was small.

As well as using PREFMAP to generate ideal points, ideal points could be determined from ratings of an ideal brand on the semantic scales.[24] Figure Five shows the rated ideal position. Its position is consistent with the PREFMAP derived ideal point.

Probability of Purchase

Given the aggregate estimates of brand coordinates and ideal points for a market, the next task is to estimate the parameters of the function linking trial and repeat to the distances from the ideal point to a brand (α_0, α_1, $\tilde{\alpha}_0$, $\tilde{\alpha}_1$ see equations 5 and 7). Base survey data on existing brands is used to generate initial estimates of the parameters. These estimates are then confirmed or revised by analysis of the concept awareness and in home use data.

In estimating the parameters, care must be taken to realize that the joint space maps reflect a market description assuming all brands are evoked. This is because in cases where the evoked set varies in composition (see Table One) only perceptual and preference judgments are obtained from individuals for their evoked set. The joint space maps based on this data therefore represent the average market perception under full evoked conditions.

The parameters linking distance to probability of choice are obtained by a regression of the percent of people who chose the brand at the end of the survey adjusted for evoked set differences versus the distance from the ideal point to the brand.

$$(10) \quad c_b/e_b = \alpha_0' + \alpha_1' \hat{d}_b^2$$

c_b = percent of people who chose brand b at the end of the interview

e_b = percent of people who evoked brand b (note in the awareness and user's surveys all respondents will evoke the new brand)

$\hat{d}_b^2$ = standardized squared distance from ideal point to brand b (see equation 6 for definition of d)
$= (d_B^2 - \bar{d}^2)/\sigma_d$

$\bar{d}^2$ = mean of $d_b{}^2$

σ_d = standard deviation of d^2

Dividing the percent who chose the brand by the percent who evoke the brand provides an estimate of propensity to choose the brand if all people evoked it. Distances are standardized across brands so that regressions can be made across different homogeneous perception or preference groups and thereby increase the number of degrees of freedom.

Table Five presents the results of the regression of the beer data and three other products. The fits are good and compare favorably to other attempts to link attitude to brand choice.[25] All the coefficient

TABLE FIVE: REGRESSION RESULTS

	Adjusted* R^2	α'_1	α'_0	t	Degrees of Freedom
Beer	.87	12.5	-13.3	6.91	6
Skin Care Product	.68	21.0	-16.9	6.25	11
Over the Counter Medicinal	.94	36.3	-15.8	9.63	5
Pain Relief Product	.81	28.7	-16.1	5.71	6

*Adjusted for degrees of freedom.

estimates are significant at the 5 percent level and the α'_1 coeficients are surprisingly similar across the three products.

The final part of the regression analysis of the beer data was to confirm the advantage of using Phase I PREFMAP rather than Phase II. When the overall regression was run on the basis of Phase II distances the R^2 dropped from .89 to .76 and the t statistics dropped over one third. The choice of Phase I appears to have been justifiable on the basis of overall fit to product choice.

Concept Awareness and in Home Placement Data

The previous sections have described the analysis of base survey data. These estimates allow examination of the feasibility of various concept positions by identifying areas of high preference where few other brands exist. This activity, in combination with creative introspection on the market, R & D inputs, and consumer group sessions should result in the specification of an initial concept. This concept is presented by consumers and the physical product is placed in the homes of consumers. The measurement section described the survey data collected from these two groups. The procedures for analysis of the concept awareness and survey data are the same as for the base data. After the joint maps and distance functions for the two groups have been estimated, attention is directed at the differences between these maps and the base maps. For example, did exposure to the concept change the dimensionality of the market perception or the positions of existing brands? In most situations the newness of the concept will not be great enough to cause such changes in perception. However, the perception of the new brand itself is likely to change between the concept awareness and usage maps. This is because expectations set up by exposure probably will not exactly match product use experience. In addition, ideal point positions may change. For example, using a spray powder deodorant may affect preference so that the derived preference ideal point shifts towards a dryness dimension.

The difficulty in this analysis is knowing what are real differences between the base, concept aware, and user maps. The decision to pool data versus retaining differences is largely judgmental since few statistical tests are available.

The output of the estimation procedures are the brand coordinates for the concept aware and user maps, ideal point coordinates, and distance function parameters. These estimates supply the needed parameter values for the model to predict trial, repeat, and market share.

MODEL TESTING

The beer data cited as examples of suggested estimation procedures were not collected in a new product situation. However, data for a new product and other new product histories allowed predictive and structural tests.

Predicting trial and Repeat: Data for a new personal care product were collected and used for prediction of trial and repeat fractions for five new concepts. The ratings for each new concept on semantic scales were obtained from separate samples of 30 people made aware of a concept. These ratings plus the factor score coefficients obtained from a factor analysis of ratings from a base survey of only the existing brands were used to specify the new conept positions on the base map (see equation four). The ideal point and distance function parameters obtained from analysis of the base survey were used to predict the new brand trial percentages. The observed trial was the percent of people in each sample selecting the new concept after having been made aware. Table Six presents the results. The average of the absolute deviations in trial is .04 or 10% of the average trial rate and none of the differences between predicted and observed are significantly different at the 10 percent level.

A test of prediction of repeat rates was conducted for the same concepts based on ratings of the brands after use. These ratings were used to define the brand positions on the base map. Since the brands tested were radically new in physical properties, usage shifted the ideal point position. The prediction was made based on factor score coefficients and distance function parameters from the base survey, but with the new ideal point location. Table Six presents the results. The average of the absolute deviations in repeat rates is .067 or 11% of the average repeat rate and none of the differences between predicted and observed are significant at the 10 percent level. Note that 70% of the differences between pairs of concepts were significant at the 10% level. The model's ability to predict trial and repeat seems to be adequate.

Markov Structure.

In considering the macro structure of the model, Parfitt and Collins' work was cited as indicating that a good estimate of long run share can be obtained by multiplying cumulative trial times the share for those who have used a new product. It remains to be shown that the simple Markov

Table Six: Prediction of New Concept Trial

	Predicted Trial (q)	Observed Trial
Concept A	.26	.27
Concept B	.37	.36
Concept C	.30	.35
Concept D	.45	.35
Concept E	.26	.31

Prediction of New Concept Repeat

	Predicted Repeat (P_{11})	Observed Repeat
Concept A	.41	.41
Concept B	.47	.50
Concept C	.45	.48
Concept D	.74	.61
Concept E	.65	.74

model proposed in this paper is a reasonable predictor of the share of purchases of those who have tried.

In order to carry out this test, it would be best to have the test market shares of the concepts described in Table Six. However, these concepts have not been introduced yet and all of them will not be introduced. As a surrogate test of the reasonableness of the macro structure, several other products that have been test marketed were examined. The long run trial and repeat probabilities measured for these brands in test market were substituted in equations one and three to obtain a predicted share. This was compared to the observed test market share. Trial and repeat data were available to the author on other new products in national markets, so a comparison of actual and predicted share could be made. Table Seven describes the data and results. The average deviation is .7 share points.

TABLE SEVEN: REASONABLENESS OF MACRO STRUCTURE

New Product	Long Run Trial (t)	Repeat Rate (P_{11})	Non-Repeat(P_{21})	Predicted Share (m)	Actual Share
Skin Care Product	.12	.75	.20	5.3%	5.9%[1]
Toilet Soap	.35	.13	.13	4.6%	5.0%[1]
New Hand Lotion	.68	.55	.38	29%	27% [2]
Over the Counter Medicinal	.32	.6	.2	10.6%	10%[1]
Specialty Cake Mix	.20	.5	.2	1.1%[3]	1.3%[1]
Cereal	.1	.5	.1	.4%[4]	.5%[2]
Shampoo	.22	.46	.12	8%[3]	7%

[1]Test market share 12 months after introduction

[2]National share 12 months after introduction

[3]Adjusted for frequency of purchase of new product relative to regular existing brands

[4]Cereals tend to be purchased in a cycle of multiple brand purchases. The share of purchases reported is the share for this brand assuming only one brand is purchased in a cycle, divided by the average number of brands purchased per cycle.

Trial Structure:

Table Six indicated that the trial propensity in the concept test group could be reasonably predicted given brand ratings. The linkage of the trial propensity in the concept test to cumulative trial will now be examined. Table Eight shows the translation of intent given awareness into an estimate of cumulative trial for five products where test market data was available on initial intent given brand awareness, aided brand awareness, distribution and observed trial. The estimated trial (see equation 2) is compared to observed trial.

Table Eight: Reasonableness of Trial Structure

	(q) Intent to try Given Awareness	(w) Aided Brand Awareness	(v) 12 month distribution	(t) Estimated Trial by Awareness	(t') Estimated Trial with Sampling	Observed Trial
Skin Care Product	.12	.45	.8	4.3%	4.3%	4.2%
Cereal	.54	.50	.7	18.9%	18.9%	17 %
Shampoo	.37	.60	.98	21.8%	21.8%	23 %
Cake Mix	.28	.65	.80	14.5%	18.8%	18 %
Toilet Soap	.33	.75	.95	23.5%	33.0%	35 %

The observed trial is based on telephone surveys or panel data which are subject to sampling variation. For the first three products the estimated and observed values agree. In the last two products adjustments must be made since extensive sampling was utilized to produce trial. Trial due to sampling was estimated by:

(11) $t'' = nu$

t'' = trial generated by sampling

n = fraction of target group sampled

u = fraction who use sample

The total trial was estimated by

$t' = t + t'' - tt''$

t' = total long run trial

t = trial by awareness

= qwv (see equation 2)

This formulation assumes awareness and sampling to be independent. This probably is reasonable since sampling is usually random within the target group. After adjustments for sampling, the predicted and observed shares are consistent. In general, the trial structure of initial intent given awareness times aided brand awareness and distribution seems to be appropriate.

Source of Share Structure: The final test of the model was a preliminary test of the structure to describe the source of the new products share (Equation 8). Table Nine shows the shares of purchases before and after a new product purchase opportunity was given to a group of 150 consumers who had previously not tried the new brand. The predicted probability is based on drawing most share from brands highly evoked and perceptually similar to the new brand (see Equation 8). The observed and predicted show good agreement. The mean absolute deviation is 1.5 share points and the majority of the new brand share is correctly predicted to come from the brand (brand 1) most widely evoked and most perceptually similar to the new product.

Table Nine: Source of New Brand Share

Existing Brands	Share of Last Purchase	Observed Share	Predicted Share
1	.409	.232	.204
2	.098	.081	.082
3	.065	.032	.054
4	.016	.016	.011
5	.049	.042	.042
6	.164	.094	.123
7	.049	.034	.044
8	.032	.008	.027
9	.016	.019	.014
10	.098	.043	.083
New Brand	0	.33	.33

These initial tests of the model lend support to the probability of purchase, market share, trial and source of share structures.

MANAGERIAL IMPLEMENTATION

This section will describe how the model and its supporting empirical analysis could be used by managers. Figure Six depicts a typical series of steps in a PERCEPTOR implementation.

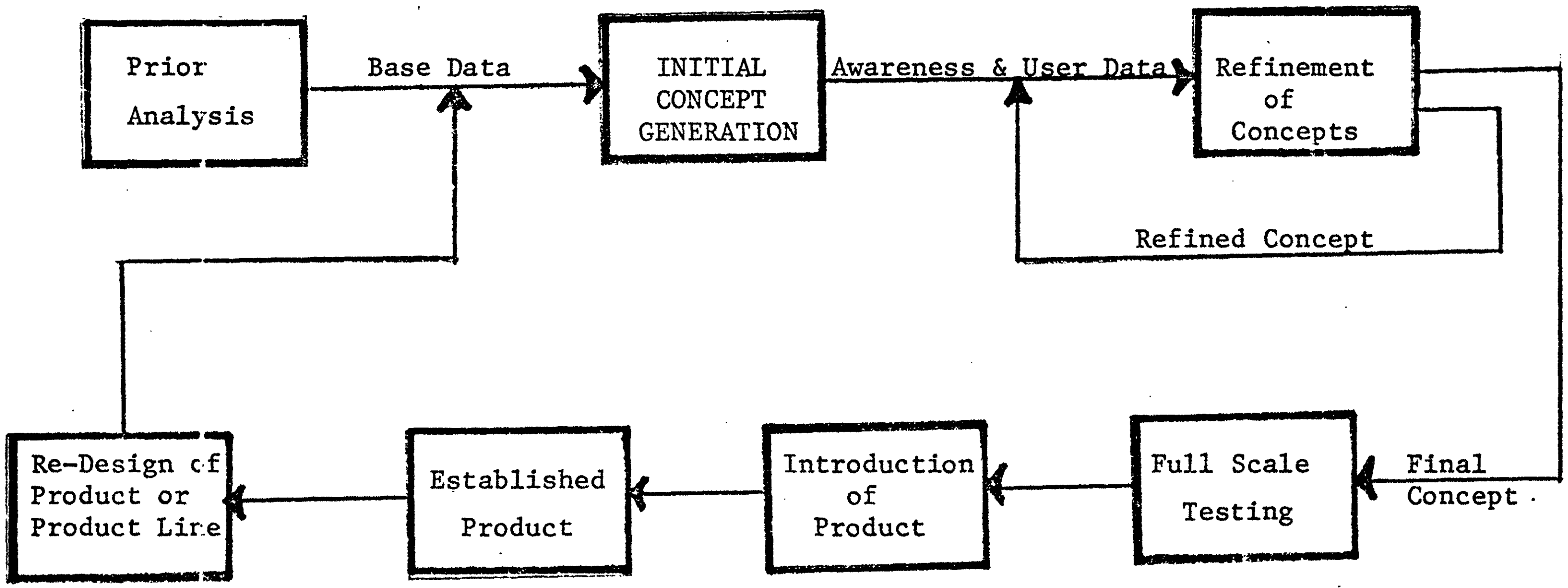
Prior Analysis

First past data and manager's ratings of brands and similarity judgments are used to generate prior maps and identify prior notions of the semantics to be used for ratings. It is useful to generate maps from managerial judgments since subsequent comparison to consumer based maps can be a very good learning experience.

Initial Concept Generation

The exploratory and base surveys allow estimation of joint space maps of the existing market structure (see measurement and estimation sections). These maps provide the managers with an understanding of (1) the underlying dimensionality of the market along with verbal interpretation of the dimensions, (2) the positions of existing brands in this market, (3) the areas of high preference, (4) the sensitivity of probablility of purchase to a brand's distance from the ideal point, and (5) the existence of homogeneous perception and preference groups. With this knowledge, effort can be directed at finding a product concept that would place itself in a unique area of high preference. For example, inspecting the base survey beer map in Figure Five would indicate that a young and

FIGURE SIX: PERCEPTOR IMPLEMENTATION



swinging beer that was not too strong could have high potential. This search for areas of concept potential can be made more formal by assuming the base map coordinates, ideal points, and distance parameters are appropriate for the trial and repeat models. Then by positioning a new brand on the trial and repeat maps, the market share can be simulated in an on-line computerization of equations 1-9. The new position could be defined by specifying the coordinates of the brand or if factor analysis was used to develop maps, by specifying an average rating profile for aware and user groups (see equation four). Simulations with this model along with creative introspection should lead to an attractive initial concept. In many cases a rough concept will already exist. In fact, it may be the excitement of this concept that precipitated the desire for a detailed product positioning study.

Design of Refined Concept

Based on the initial concept, awareness and in home use surveys are conducted and joint maps estimated for the trial and repeat models (see equations 4-7 and estimation section.) Differences in dimensionality, brand positioning, or ideal points will supply managers with insight into the effect of the brand on perception and preference structures. The new brand position is now empirically determined on the user and repeat maps. This information is important in determining if the product delivers its promised benefits. If very high expectations are created for the brand, but not made real by usage, the product may be rated lower than if achievable expectations were fostered by the concept statement.[26]

With the empirically specified trial and repeat model, improved product positioning can be simulated by the PERCEPTOR computer model.

At this point, reference trial and repeat rates are known for the initial concept. Therefore, the equations to predict trial and repeat are modified so that estimates of trial and repeat for refined concept positions are made based on proportional changes from the reference values. This makes the model more robust. For long run trial given awareness and availability (q):

$$(12)\quad q = \bar{q}\ \frac{q'}{q''}$$

$\bar{q}$ = observed reference trial propensity in concept aware group

q'' = estimated long run trial specified by $\alpha_0 + \alpha_1 d_B^2$ where d_B^2 = the distance squared from the reference concept to the ideal point

q' = estimated long run trial specified by $\alpha_0 + \alpha_1 d_B^2$ where d_B^2 = the distance squared from the refined concept to the ideal point

$0 \leq q \leq 1.0$

Similarly, for the repeat probabilities:

$$(13)\quad p_{11} = \bar{p}_{11}\ \frac{p'_{11}}{p''_{11}}$$

$\bar{p}_{11}$ = observed reference repeat probability in user group

p''_{11} = estimated repeat probability specified by $\tilde{\alpha}_0 + \tilde{\alpha}_1\ \tilde{d}_B^2$ where $\tilde{d}_B^2$ is the distance squared from the reference concept to the ideal point

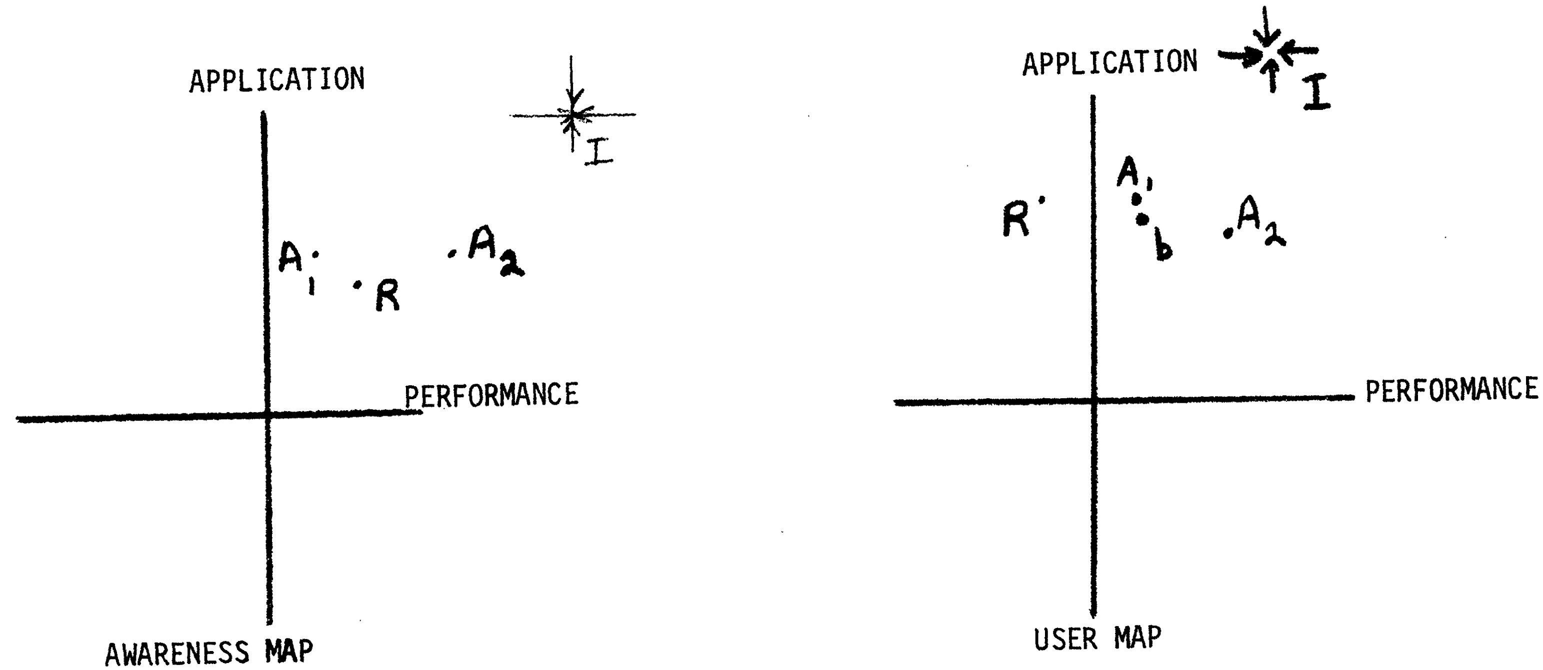
p'_{11} = estimated repeat probability specified by $\tilde{\alpha}_0 + \tilde{\alpha}_1\ \tilde{d}_B^2$ where $\tilde{d}_b^2$ is the distance squared from the refined concept to the ideal point

$0 \leq p_{11} \leq 1.0$

Given the fully parameterized model, alternative concepts can be simulated until a best product positioning is identified. Figure Seven describes the new brand and ideal point positions on the map for concept aware and user groups of a new personal care product. The reference concept was perceived as good on both the application and performance dimension based on awareness, but after use, its position shifted to a lower score on performance and higher score on application. The advertising claims of performance were not fulfilled by the product. In fact, based on usage, the product with a concept description was significantly less preferred than the product with no concept claims (i.e. "blind test"). Also note that the ideal point shifted more toward the application dimension. This initial concept generated trial and repeat probabilities that implied a five percent market share. Two alternate positions were simulated. The first represented a strategy of aligning the product claims and performance. This is indicated by A_1 in Figure Seven. A_1 is shown roughly corresponding to the blind product position in the user map. The share associated with this positioning was six percent. The second strategy was to improve the copy execution in terms of expectations of performance and physically improve the product so it would also move on the performance dimension. This strategy is indicated by A_2 and implied an 8 percent market share. These simulations indicated substantial gains could be made by improving the positioning. This led to changes in the product advertising and additional R & D effort to improve the perceived product performance.

This brief description is an example of concept refinement procedures using PERCEPTOR. It should be emphasized that the model is a complement

FIGURE SEVEN: EXAMPLE OF CONCEPT REFINEMENT



R = Reference concept
A_1 = Alternate position one
A_2 = Alternate position two

I = Ideal point

b = Blind product use

and not a substitute for the creative ability of the manager. Although the model may indicate good positions, the man must create the physical product and advertising execution that will position the product at the desired location.

After new designs have been developed, usually new perception, preference and choice data would be collected to determine if the new designs actually position themselves as desired in the consumer's mind.

Full Scale Test and Introduction

After the best design has been developed, additional testing may be appropriate. For example, test marketing or a laboratory test market simulation would be appropriate at this point for many frequently purchased consumer goods. PERCEPTOR would not be the best model to use during an actual test market. A detailed diffusion model such as SPRINTER would be better for interpreting the test data, refining the marketing strategy, and aiding in the go/no introduction decision.[27]

Established Product and Redesign

Assuming the product has been successfully launched, models such as BRANDAID could be used to formulate annual plans and develop a detailed specification of the mix of marketing strategy variables.[28] PERCEPTOR could be used to consider repositioning or redesigning of the established product. This would cause a feedback to the design simulation step of the implementation process.

Application in four new product situations indicates the use of PERCEPTOR as described in Figure Six provides managers with a better understanding of the perception, preference, and purchase structure of their markets, specifies measurement needs, serves as a structure to interpret experimental results, and aids managers in creating successful new product designs.

FUTURE WORK

The first focus of future work will be to apply the model to more real product situations and to perform additional predictive tests. During this process new implementation experience will be gained, the appropriateness of the suggested application procedure will be accessed, and the managerial impact will become more apparent.

In addition to predictive tests, comparisons to other model structures will be undertaken. One step has been taken in this direction. In the beer data the joint space model was compared to a model of preference as a function of brand ratings and probability of purchase as a function of preference. The equations were:

$$(14) \quad g_{ib} = \beta_0 + \beta_1 f^*_{1ib} + \beta_2 f^*_{2ib}$$

g_{ib} = preference data for individual i and brand b (obtained by constant sum procedures)

f^*_{yib} = factor score on dimension y for individual i and brand b

$\beta_0, \beta_1, \beta_2$ = estimated coefficients

and

$$(15) \quad p^*_{ib} = 1/(1 + e^{-\gamma}\, g_{ib}^{-\Delta})$$

p^*_{ib} = probability of purchase of brand b by individual i.

γ, Δ = estimated coefficients

The first equation linearly relates ratings to preference. A non-linear form of equation 14 was specified by replacing g by e^g. The second is a logit relationship between probability of purchase and preference. The logit is "s" shaped and asymptotically approaches values of 1.0 for high values of preference and zero for low values of preference. Equation 15 can be equivalently written in a log-linear form as:

$$\text{(15A)} \quad \log (p^*_{ib}/(1 - p^*_{ib})) = \gamma + \Delta \log g_{ib}$$

Table Ten presents the equation 14 regression results on the individual beer data. The F's were significant at the 1% level, but the R^2 were low. The highest value was .34. Little gain was made with the non-linear form. The first factor score coefficient (young, modern, swinging dimension) was signficant at the 1% level and approximately .6 in both regressions. The coefficient for factor two was not significant at 10% level. These fits do not appear to be as good as those of the joint space model which yielded 76% (phase I) to 53% (phase III) in fitting to preference data (see Table Four).[29] One explanation of

TABLE TEN: REGRESSIONS FOR ADDITIVE MODELS

	R^2	F(2,357)	$\hat{\beta}_1$	t_1	$\hat{\beta}_2$	t_2
Linear	.32	84.1***	.60	12.9***	-.20	.43
Non-Linear	.34	92.1***	.57	13.4***	.039	.95

* = significant at 10% level

** = significant at 5% level

*** = significant at 1% level

the lack of fit of the linear additive model could have been that the reduced space factor scores resulted in a loss of information. However, a regression against the raw brand ratings data on the 17 scales had an R^2 of only .39 and a R^2 of .37 was found when the regression was done for only the ten scales that loaded most heavily on the factors. Allaire has tested some additional alternate structures with the beer data including linear and non-linear discrepancy models.[30] These utilized the differences between the ideal ratings and the actual ratings as independent variables in the regression against the preference data. In no case did he find an R^2 greater than 30 percent for discrepancy models.

Although the fits for equation 14 were not good, equation 15 performed very well. All the preference data was rank ordered and then divided into ordered groups of 25 respondents. In each group of 25, the average preference score and the fraction of people who purchased was determined. Forty observations of preference and probability of purchase were used in a regression of equation 15a. The R^2 was 88 percent and the coefficients were significant at the 10% level. This compares very favorably to the fits reported in Table Five.

The initial test of the alternate structure in equations 14 and 15 indicates this structure is adequate, but not as attractive as the model postulated in this paper. Although the preference to purchase link is good, the perception (ratings) to preference linkage is characterized by high variance. The model in equations 14 and 15 also lacks the managerial appeal of maps and spacial representation of a market.

These preliminary alternative model tests and the predictive market share testing reported earlier in this paper have increased the author's prior probabilities that the PERCEPTOR structure is good, but additional testing will be carried out before the model validation process is complete. It should be pointed out however, that the model is trying to provide a basis for product positioning and is not trying to eliminate test marketing. In this context, the use of estimated share is a measure of relative rather than absolute potential of new concepts. The objective is to find and refine product positions. It should also be remarked that although this model may not be valid as an individual model of choice behavior, it should be a useful aggregate description of market response. Future applications of the model should help determine the model's accuracy and managerial value.

A number of model evolutions are being considered. First, the Markov model could be extended to a full matrix of all the major brands in the market rather than just the two state "us" and "them" model. In this structure, the distances from the ideal point would determine repeat rates and the distances between brands (see equation eight) would specify how the non-repeat probability was divided into switching rates to specific brands. This full matrix model would allow product positioning of a new brand to affect the non-repeat (p_{21}) as well as repeat (p_{11}) probabilities. In addition with the full matrix, multi-brand position changes could be simulated and product line additions and deletions could be accessed. The disadvantage of the full matrix model is that large sample sizes would be required. The full matrix would be most feasible in the case of re-aligning a product line based on a history of brand switching for existing products.

Another direction for future work is the application of the model structure to durable goods. This probably would entail a substantially different flow (e.g. include shopping behavior), but the underlying notion of linking perceptual maps to purchase probabilities may be useful. It is anticipated that in the long run, special model structures would be needed in order to maximize the data measurement environments of various industries and to capture the critical aspects of product design in each industry.[31]

This paper represents a first step in applying management science to aid managers in the design of products. Future work will determine if the potential identified here is real and can be applied across many industries.

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FOOTNOTES

1. See Glen L. Urban, "SPRINTER mod III: A Model for the Analysis of New Frequently Purchased Consumer Products, "Operations Research, Vol.18, (September-October 1970), pp. 805-853 or William F. Massy, "Forecasting the Demand for New Convenience Products," Journal of Marketing Research, Vol. VI, (Nov. 1969), pp. 405-413 or Henry J. Claycamp and Lucien E. Liddy, "Prediction of New Product Performance: An Analytical Approach," Journal of Marketing Research, Vol VI, (Nov. 1969), pp. 414-421.

2. Volney Stefflre, "Market Structure Studies: New Products for Old Markets and New Markets (Foreign) for Old Products," in Frank Bass, Charles King, and Edgar Pessemier, eds., Applications of the Science in Marketing Management, (New York: John Wiley, 1968), pp. 251-268.

3. See "Maxwell House Division" in Milton Brown, et al, eds., Problems in Marketing, (New York: McGraw Hill, 1968), pp. 439-465.

4. Paul E. Green and Frank J. Carmone, Multidimensional Scaling and Related Techniques in Marketing Analysis, (Boston, Mass.: Allyn and Bacon, Inc., 1970) and Paul E. Green and Vithala R. Rao, Applied Multi-Dimensional Scaling, (New York: Holt, Rinehart, and Winston, Inc., 1972) p. 125.

5. Edgar A. Pessemier, "Multi-Attribute Choice Theory - A Review and Analysis, " Paper No. 372, Herman C. Krannert School of Industrial Adeministration, Purdue University, 1972.

6. J. H. Parfitt and B. J. K. Collins, "The Use of Consumer Panels for Brand'Share Prediction," Journal of Marketing Research, (May 1968), pp. 131-146.

7. The equilibrium share is obtained from the equilibrium definition:

$$\begin{vmatrix} m_1 m_2 \end{vmatrix} \begin{vmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{vmatrix} = \begin{vmatrix} m_1 m_2 \end{vmatrix}$$

where m_n = equilibrium market share for firm n.

$n = 1$ denotes our firm

$n = 2$ denotes all other firms

then $m_1 p_{11} + m_2 p_{21} = m_1$

$m_1 p_{12} + m_2 p_{22} = m_2$

and $m_1 + m_2 = 1.0$

Solving for m_1 yields

$$m_1 = \frac{p_{21}}{1 + p_{21} - p_{11}}$$

8. See Glen L. Urban, "SPRINTER mod III: A Model for the Analysis of New Frequently Purchase Consumer Products," Operations Research, Vol. 18, (September-October 1970), pp. 805-853.

9. J. D. Carroll and J. J. Chang, "Relating Preference Data to Multidimensional Scaling Solutions via a Generalization of Coombs' Unfolding Model," Bell Telephone Laboratories, Murray Hill, N. J., 1967 (mimeographed) and J. D. Carroll, "Individual Differences and Multidimensional Scaling," in R. N. Shepard, A. K. Romney, and S. Nerlove, eds., Multidimensional Scaling: Theory and Application in the Behavioral Sciences, (New York: Academic Press, 1972), pp. 105-157.

10. See J. D. Carroll and J. J. Chang, "Analysis of Individual Difference in Multidimensional Scaling Via an N-Way Generalization of 'Eckart-Young' Decomposition," Psychometrika, Vol. 35, (September 1970), pp. 283-319 and L. R. Tucker and S. Messick, "An Individual Differences Model for Multidimensional Scaling," Psychometrika, Vol. 28 (1963), pp. 333-367.

11. See Paul E. Green and Frank J. Carmone, Multidimensional Scaling and Related Techniques in Marketing Analysis, (Boston, Mass.: Allyn and Bacon, Inc., 1970) and Paul E. Green and Vithala R. Rao, Applied Multi-Dimensional Scaling, (New York: Holt, Rinehart, and Winston, Inc., 1972) for a full discussion of the use of such procedures.

12. Paul E. Green and Vithala R. Rao, Applied Multi-Dimensional Scaling, (New York: Holt, Rinehart, and Winston, Inc., 1972), p. 125.

13. If the derived weights from PREFMAP are negative, the unweighted distance between brands must be used.

14. See Paul E. Green and Frank J. Carmone, Multidimensional Scaling and Related Techniques in Marketing Analysis, (Boston, Mass.: Allyn and Bacon, Inc., 1970) and Paul E. Green and Vithala R. Rao, Applied Multi-Dimensional Scaling, (New York: Holt, Rinehart, and Winston, Inc., 1972) for a discussion.

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16. Data was collected by Yvan Allaire at the University of Ottawa.

17. See Warren S. Torgenson, Methods of Scaling, (New York: John Wiley, 1958), pp. 105-112.

18. See J. D. Carroll and J. J. Chang, "Analysis of Individual Difference in Multidimensional Scaling Via an N-Way Generalization of 'Eckart-Young' Decomposition," Psychometrika, Vol. 35, (September 1970), pp. 283-319 and L. R. Tucker and S. Messick, "An Individual Differences Model for Multidimensional Scaling," Psychometrika, Vol. 28 (1963), pp.333-367.

19. N. Howard B. Harris, " A Hierarchical Grouping Routine, IBM 360/65 FORTRAIN IV Program," University of Pennsylvania Computer Center, Oct.1966.

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21. David Khlar, " A Monte Carlo Investigation of the Statistical Significance of Kruskal's Non-Metric Scaling Procedure," Psychometrika, vol. 34,(September 1969), pp. 319-330.

22. See David Khlar, "A Monte Carlo Investigation of the Statistical Significance of Kruskal's Non-Metric Scaling Procedure," Psychometrika, vol. 34, (September 1969), p. 320 and Paul E. Green and Vithala R. Rao, Applied Multi-Dimensional Scaling, (New York: Holt, Rinehart, and Winston, Inc., 1972) pp. 37-48.

23. Mantilla, Luis, "Multidimensional Scaling and the Data Base", unpublished M.S. Thesis (MIT, 1973) pp. 38-49.

24. See Edgar A. Pessemier, "Multi-Attribute Choice Theory - A Review and Analysis," Paper No. 372, Herman C. Krannert School of Industrial Administration, Purdue University, 1972, for a elaborate method of rating an "ideal" brand.

25. For example, Stefflre has reported .5 to .8 correlations of inter-brand distances with switching matrices. Volney Stefflre, "Market Structure Studies: New Products for Old Markets and New Markets (Foreign) for Old Products," in Frank Bass, Charles King, and Edgar Pessemier, Eds., Applications of the Sciences in Marketing Management, (New York: John Wiley, 1968), pp. 251-268. However, Lehmann found that maps derived from switching matices did not correspond with maps obtained by processing similarity judgments in terms of either brand positions or dimensionality. Donald R. Lehmann, "Judged Similarity and Brand Switching Data as a Similarity Measures," Journal of Marketing Research, Vol. 9, (August 1972), pp. 331-335. Fits in the range .1 to .2 are reported in Jagdish N. Sheth and W. Wayne Talarzyk, "Perceived Instrumentality and Value Importance as Determinants of Attitudes," Journal of Marketing Research, 9 (February 1972), pp. 6-9. Bass reports correct prediction of first preference by a linear attitude model in the range 63% to 75%. Frank M. Bass and W. Wayne Talarzyk, "An Attitude Model for the Study of Brand Preference," Journal of Marketing Research, 9 (February 1972) pp. 93-96. The best results are reported by Pessemier. Edgar A. Pessemier, Philip Burger, Richard Teach, and Douglas Tigert, "Using Laboratory Brand Preference Scales to Predict Consumer Brand Purchases," Management Science, Vol. 17, (February 1971) pp. 371-385.

26. See Rolph E. Anderson, "Consumer Dissatisfaction: The Effect of Disconfirmed Expectancy on Perceived Product Performance," Journal of Marketing Research, Vol. X (February 1973). pp. 38-44.

27. See Glen L. Urban, "SPRINTER mod III: A Model for Analysis of New Frequently Purchased Consumer Products," Operations Research, Vol.18, (September-October 1970), pp. 805-853.

28. John D. C. Little, "BRANDAID: An On-Line Marketing Mix Model," Alfred P. Sloan School of Management Working Paper #586-72, (Cambridge, Mass.: M.I.T., 1972).

29. Equation 14 is equivalent to the equation PREFMAP phase IV applies idiosyncratically.

30. Yvan Allaire, "The Measurement of Heterogeneous Perceptual and Preference Structure," unpublished Ph.D. Dissertation (August, 1973) Sloan School of Management, M.I.T.

31. For example, in consumer durables, many attributes are not especially prone to bi-polar evaluation, but rather are integer. The frost free feature is either present or not present in a freezer. Future work will attempt to deal with these objective physical features, as well as attitudinal judgments. Green has proposed an approach for dealing with 0,1 attributes. Paul Green "Generalized Approaches to Product-Features Mapping," Working Paper, University of Pennsylvania, (April 1973).